How Deep Learning Could Predict Weather Events

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On behalf of Sa-Kwang Song, Ph.D.

Research Data Platform Center

Korea Institute of Science and Technology Information

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Outline

- Introduction: Vision vs. Meteorology tasks
- Deep Learning for Weather Prediction
  - DeepRain: Precipitation Prediction of & Next Step of Images
  - DeepTC: Tropical Cyclone Trajectory Prediction using Numerical Model Data
  - GlobeNet: Tropical Cyclone Trajectory Prediction using Satellite Images & AutoEncoder
- Conclusion

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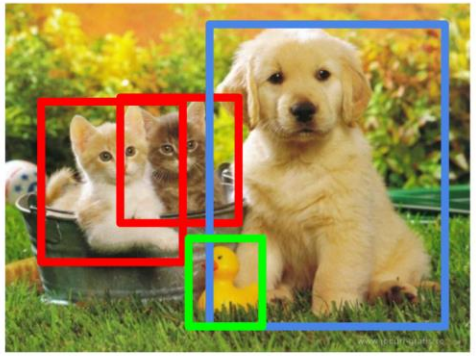
Vision vs. Meteorology Tasks

Classification

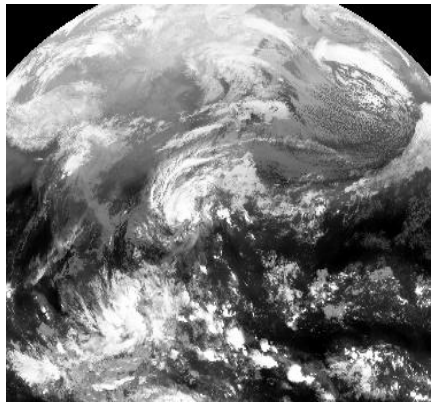
Classification + Localization

Object Detection

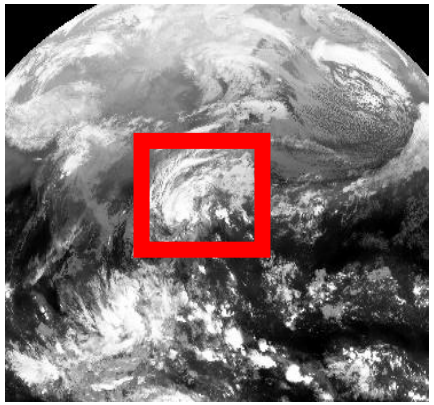


Instance Segmentation

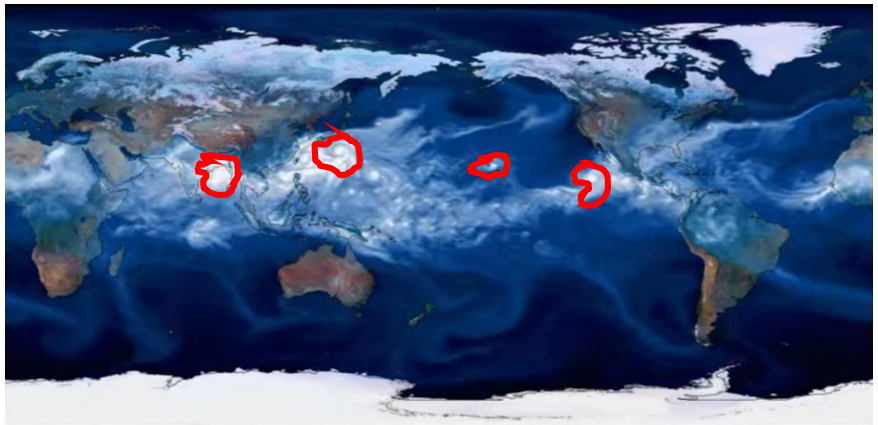
https://chaosmail.github.io/deeplearning/2016/10/22/intro-to-deep-learning-for-computer-vision/



Typhoon Classification



Typhoon Location



Weather/Climate Event Detection Or Segmentation

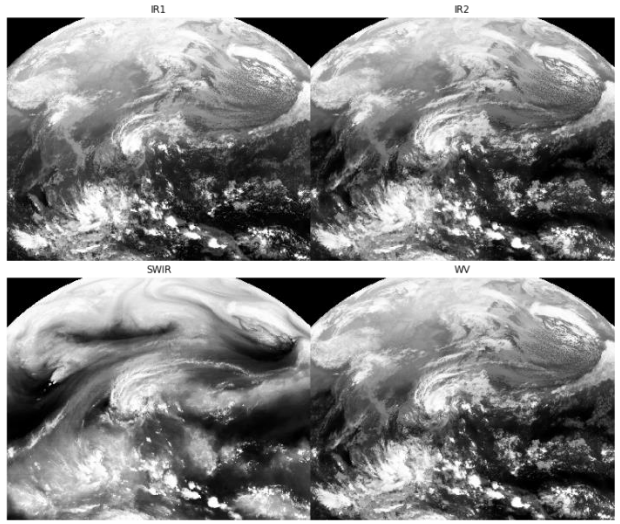
Similarities vs Differences

- Similarities
  - Tasks are similar:
    - Classification, Localization, Detection, Segmentation
    - Clustering, Regression
    - Representation Learning
- Differences
  - Unique attributes of Weather Data
    - Multi-channel/Multi-variate
    - Different Spatio-temporal scales
    - Double precision floating point
    - Underlying statistics are likely different
    - Large amount of data compared to general Vision tasks

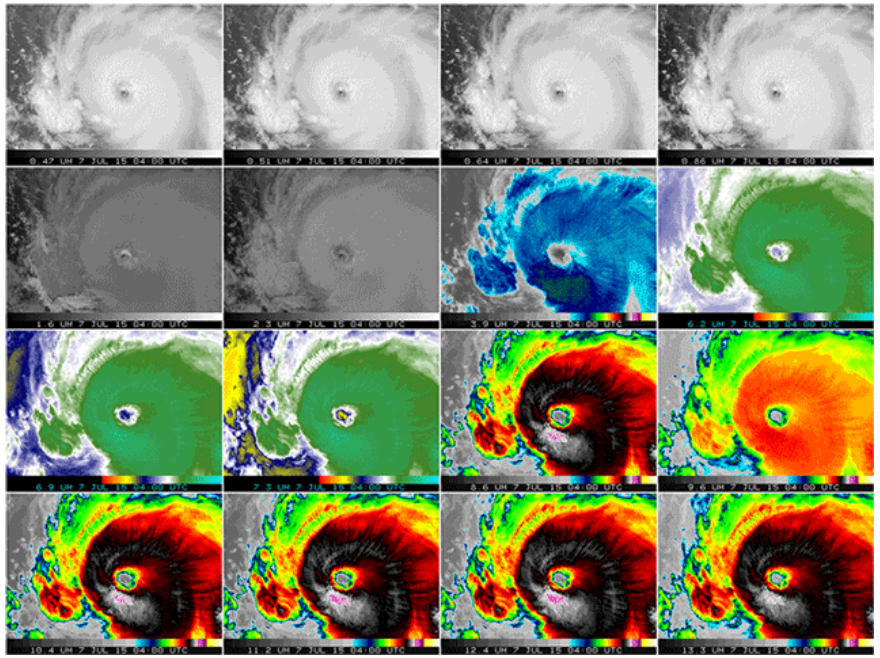
Phrabat 2017(CI 2017)

Challenge: Multi-Variate Data

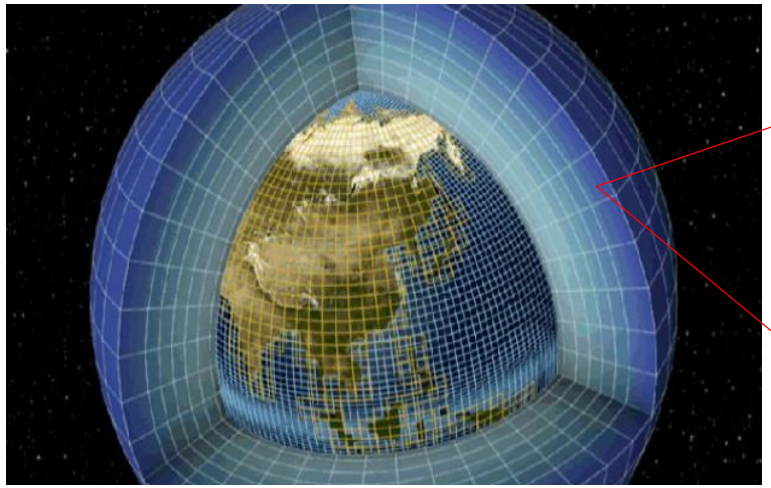
COMS Satellite



Himawari 8 satellite



WRF Result



	Name	Format	Description	Data Dim.
1	U	Time, bottom_top, south_north, west_east_stag	x-wind component	3차원
2	V	Time, bottom_top, south_north_stag, west_east	y-wind component	
3	W	Time, bottom_top_stag, south_north, west_east	z-wind component	
4	PH	Time, bottom_top_stag, south_north, west_east	perturbation geopotential	
5	T	Time, bottom_top, south_north, west_east	perturbation potential temperature	
6	P	Time, bottom_top, south_north, west_east	perturbation pressure	
7	QVAPOR	Time, bottom_top, south_north, west_east	Water vapor mixing ratio	
8	QCLOUD	Time, bottom_top, south_north, west_east	Cloud water mixing ratio	
9	QRAIN	Time, bottom_top, south_north, west_east	Rain water mixing ratio	
10	QICE	Time, bottom_top, south_north, west_east	Ice mixing ratio	
12	QSNOW	Time, bottom_top, south_north, west_east	Snow mixing ratio	
13	QGRAUP	Time, bottom_top, south_north, west_east	Graupel mixing ratio	
14	SMOIS	Time, soil_layers_stag, south_north, west_east	Soil moisture	
15	Q2	Time, south_north, west_east	Vapor mixing ratio at 2 m	2차원
16	T2	Time, south_north, west_east	Temperature at 2 m	
17	TH2	Time, south_north, west_east	Potential temperature at 2 m	
18	PSFC	Time, south_north, west_east	Surface temperature	
19	U10	Time, south_north, west_east	U at 10 m	
20	V10	Time, south_north, west_east	V at 10 m	
21	SST	Time, south_north, west_east	Skin sea surface temperature	
22	TSK	Time, south_north, west_east	Surface skin temperature	
23	RAINC	Time, south_north, west_east	Accumulated total cumulus precipitation	
24	RAINNC	Time, south_north, west_east	Accumulated total grid scale precipitation	
25	OLR	Time, south_north, west_east	TOA outgoing long wave	
26	LH	Time, south_north, west_east	Latent heat flux at the surface	
27	HFX	Time, south_north, west_east	Upward heat flux at the surface	

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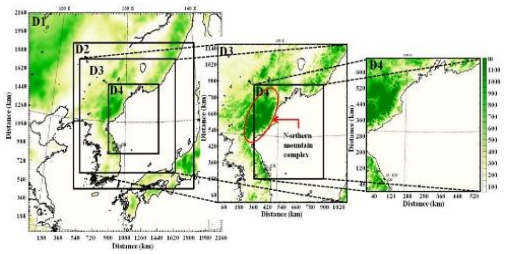
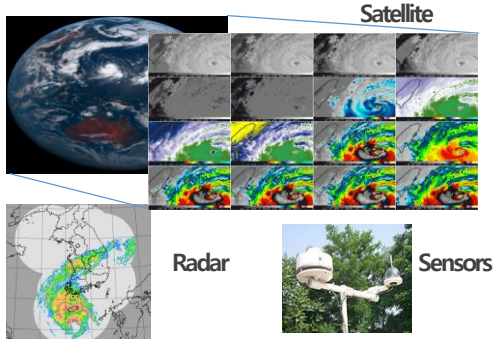
Prediction of Weather Events

Numerical Model Results

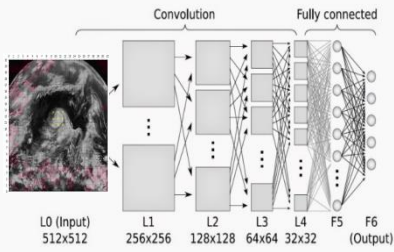


Image/Sensor Data



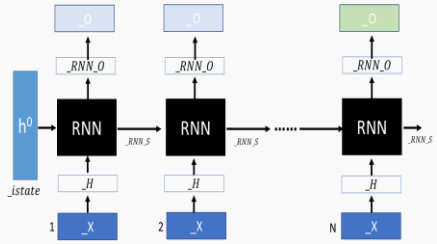
Prediction Model based on DL

Convolutional Neural Networks



+

Recurrent Neural Networks



Disaster Prediction

Typhoon/Precipitation

Flood/Surge

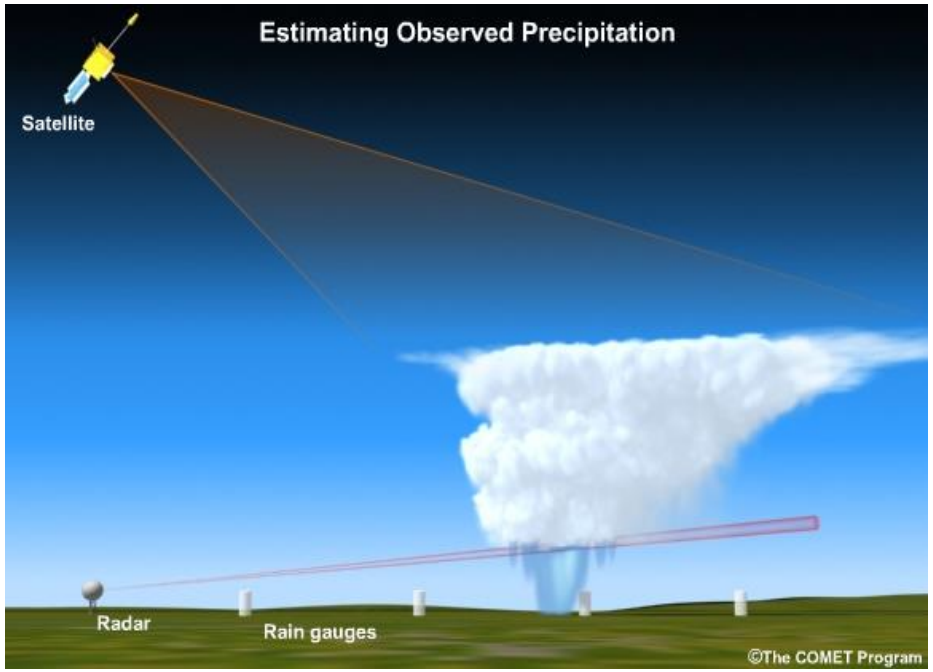
Flood Level | Surge Level

Bigdata & AI based Prediction and Analysis Platform

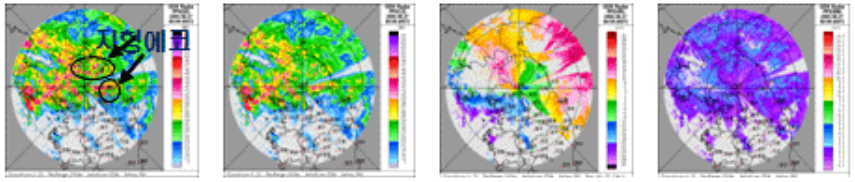
BAIPAS

Spark | Spark Streaming | TensorFlow | NVIDIA CUDA | hadoop | NotOnlySQL | kubernetes | docker

- Weather Radar Data
  - refers to data represented by **a radar image** that is composed using the *moving speed, direction, and strength of a signal* transmitted by a radar transmitter into the **atmosphere** and received after it has collided with **water vapor or the like**.



Methods used to measure precipitation



반사도 [DZ] 수정반사도 [CZ] 시선속도 [VR] 스펙트럼폭[SW]

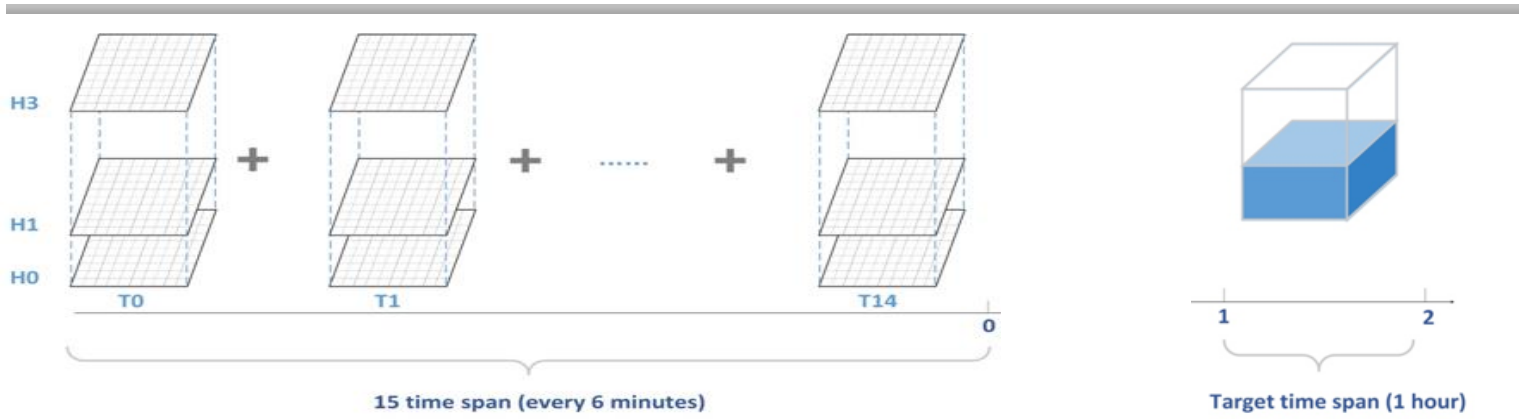
Weather Radar Center
http://radar.kma.go.kr/lecture/radar/dataflow.do

DeepRain: Precipitation Prediction

DeepRain: A Predictive ConvLSTM Network for Precipitation

1) To predict the total rainfall amount on the ground between future 1-hour and 2-hour for each target site using radar echo data.

2) To apply Convolutional LSTM(Shi et al, 2015) for 3-dimensional and 4-channel radar data for the prediction

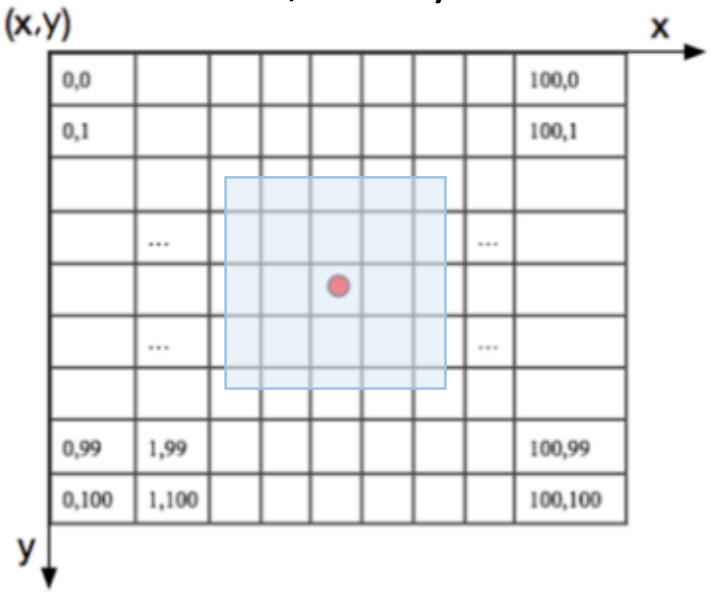


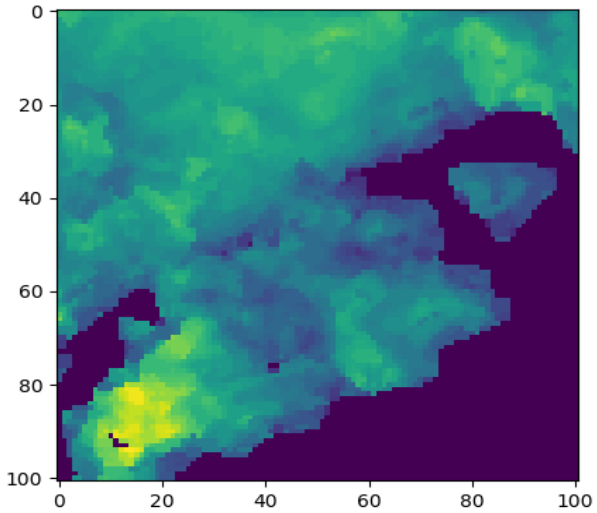
6 mins * 15 = 90 mins

DeepRain: Radar Data

- Research-use data by Shenzhen Meteorological Agency
  - Modeling specific areas in Shenzhen as **a grid pattern(101*101km²)**
    - Radar reflection values: 101*101 numerical values (dBZ) of representing each cell
    - Precipitation amount: Total amount of rainfall in target site (50*50 area from center)
  - Normalization, Anonymization

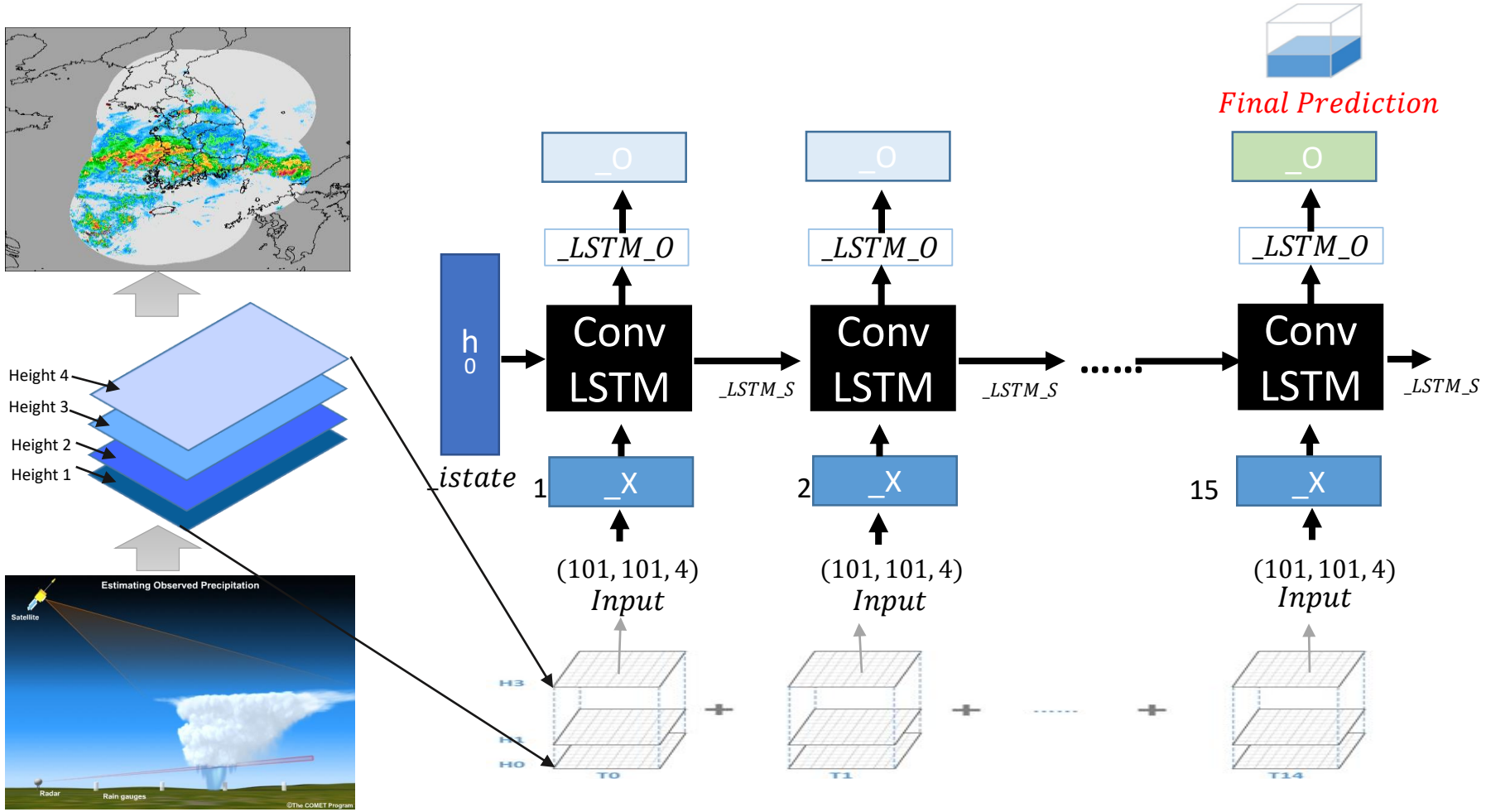
101*101km²





Shenzhen Meteorological Bureau-Alibab, "Short-Term Quantitative Precipitation Forecasting," https://tianchi.aliyun.com/competition/information.htm?spm=5176.100067.5678.2.jsxLyX&raceId=231596.

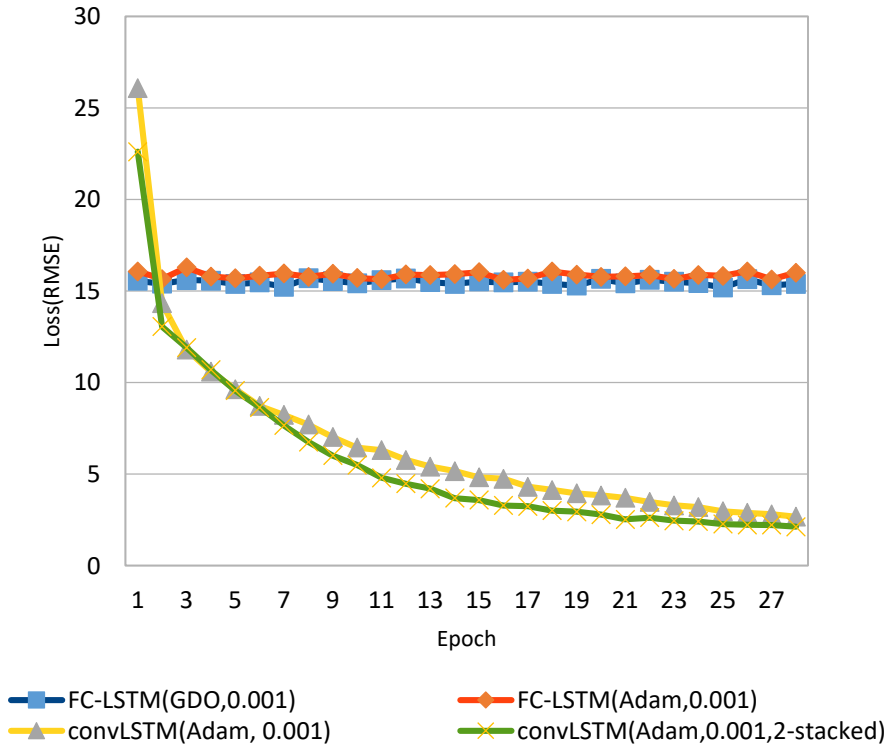
DeepRain: Precipitation Prediction



http://radar.kma.go.kr/lecture/radar/dataflow.do

DeepRain: Experimental Results

- convLSTM shows better learning performance than FC-LSTM



- Test result with Testset
  - Epoch 5

Model	RMSE	Drop Ratio
Linear Regression	14.69	-
DeepRain: FC-LSTM	14.46	1.6%
DeepRain: convLSTM	11.51	21.6%
DeepRain: convLSTM(2-stacked)	11.31	23.0%

- With two-stacked we achieved 23.0% performance increase than LR.
- Furthermore, it is lower 21.7% than FC-LSTM
- Because FC-LSTM lost spatial information

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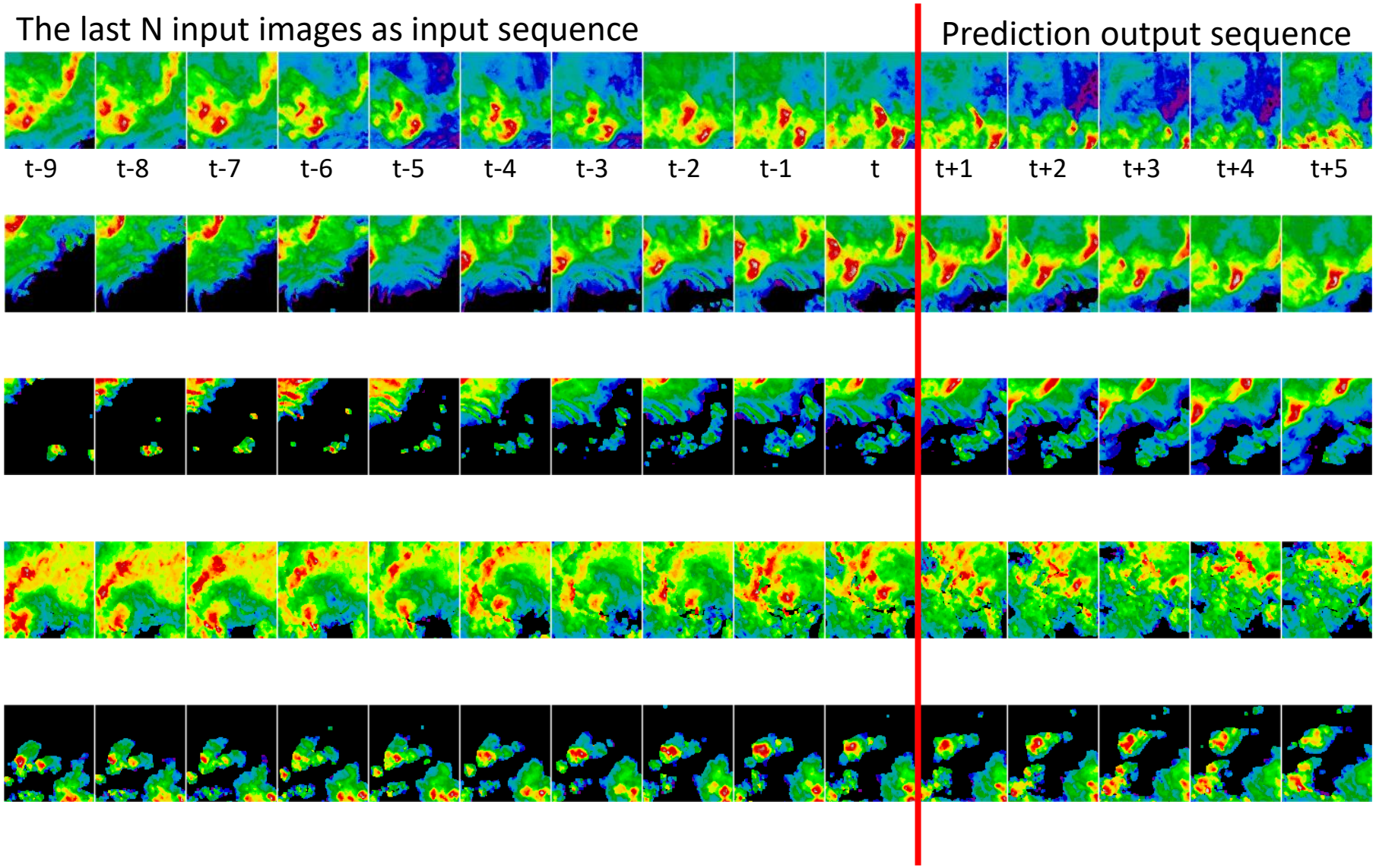
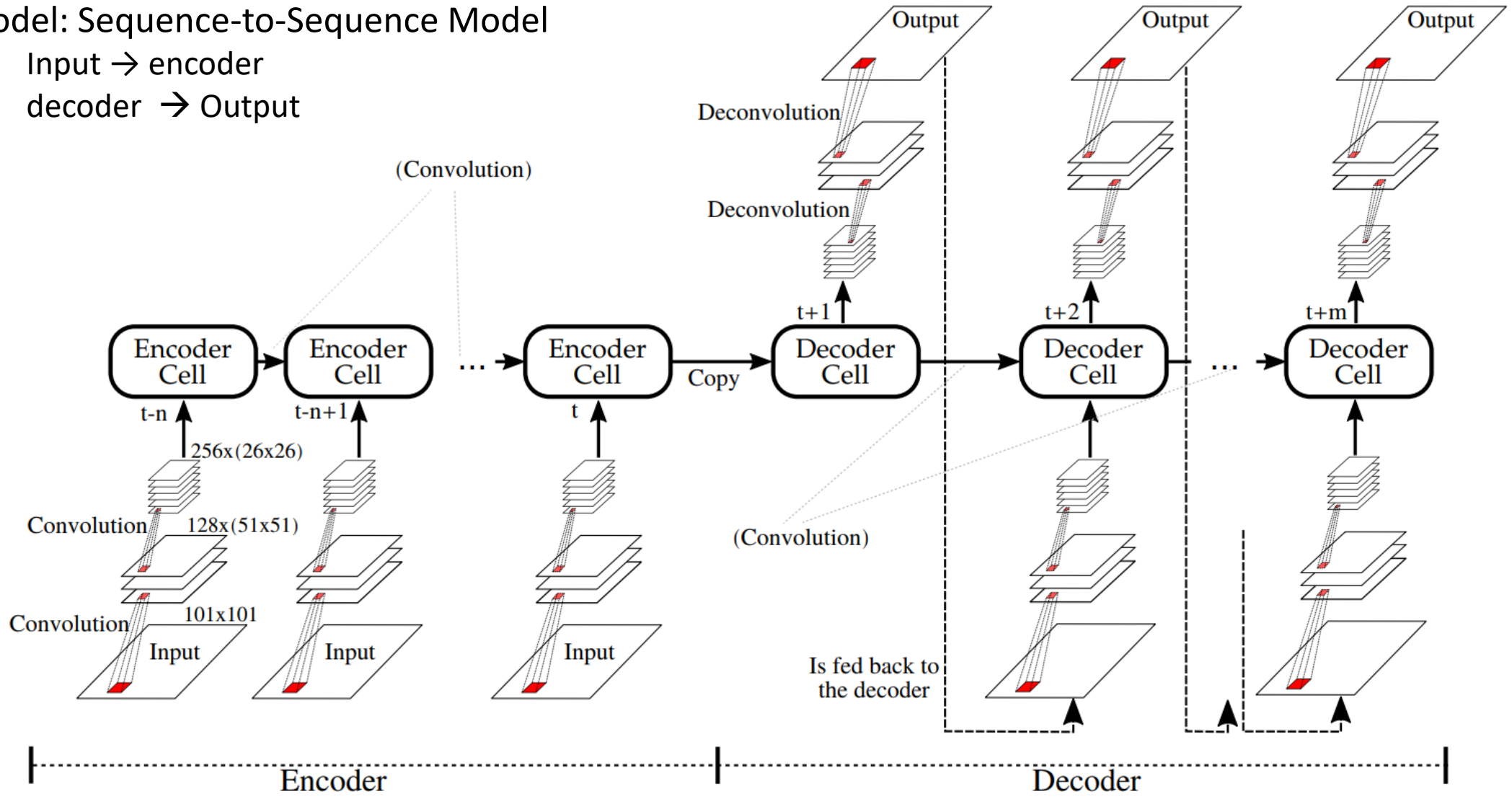
Seq-to-Seq DeepRain: Prediction of Next Seq. Image



Seq-to-Seq DeepRain: Conv2Deconv RNN/LSTM

- Model: Sequence-to-Sequence Model
  - Input → encoder
  - decoder → Output



DeepRain: Deep Learning Models

- Input and state transformation models
  1) Vanilla fully-connected models
     - Vanilla FullyConnected-RNN
     - Vanilla FullyConnected-LSTM
  2) **<u>Convolution to Deconvolution (Conv2Deconv) models</u>**
     - Convoluted RNN's states (Conv2Deconv-ConvRNN)
     - Convoluted LSTM's states and memory cells(Conv2Deconv-ConvLSTM)
  3) Full-size convolution(Input images are fed directly to the convolutional networks)
     - Convoluted RNN's states (Fullsize-ConvRNN)
     - Convoluted LSTM's states and memory cells (Fullsize-ConvLSTM)

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DeepRain: Results

	Testing Cost		Testing RMSE	
	Mean	Best case	Mean	Best case
FullyConnected-RNN	32.68	18.38	40.28	34.28
FullyConnected-LSTM	28.11	16.89	36.89	25.49
Conv2Deconv-RNN	13.68	6.86	23.15	10.80
Conv2Deconv-LSTM	**13.16**	**6.71**	**22.42**	**10.73**
Fullsize-RNN	15.14	7.00	25.35	11.25
Fullsize-LSTM	14.94	7.65	24.65	11.74

(Note: Cost = Huber Loss with $\delta = 1.0$)

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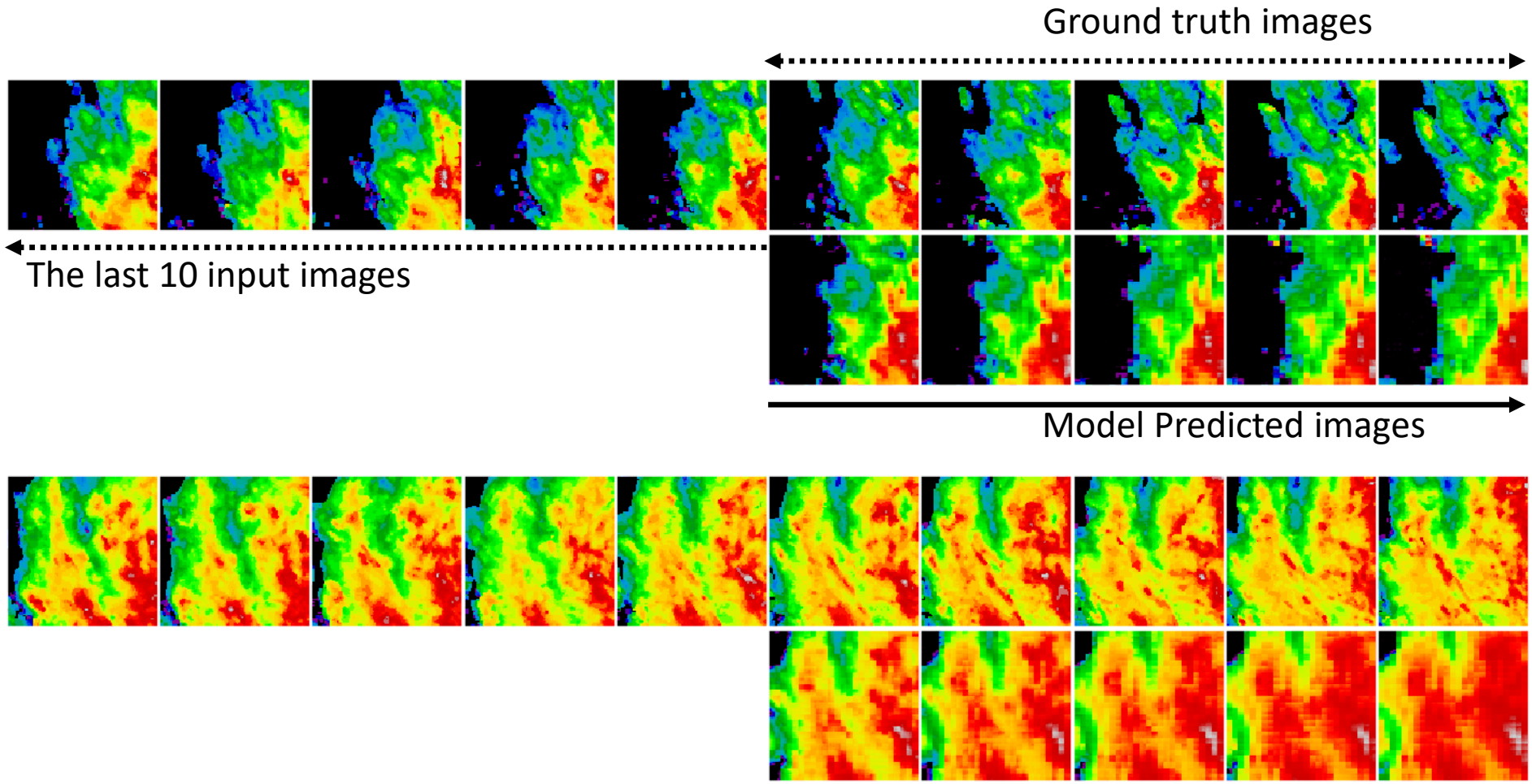
DeepRain: Conv2Deconv-ConvLSTM



→ Note: predicted images are blurred

- Testing: mean-cost=13.16, mean-rmse=22.42
- Testing: best-cost=6.71, best-rmse=10.73

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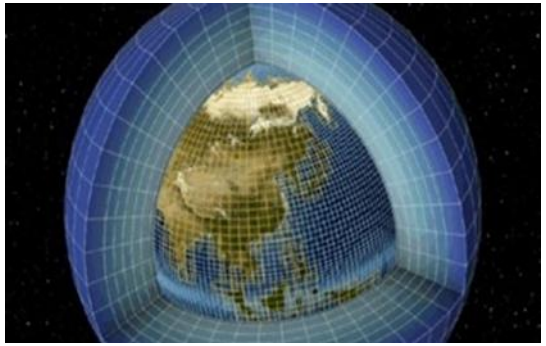
P8163 - DeepTC: GPU-Accelerated Trajectory Prediction for Tropical Cyclone using Traditional Numerical Model Data

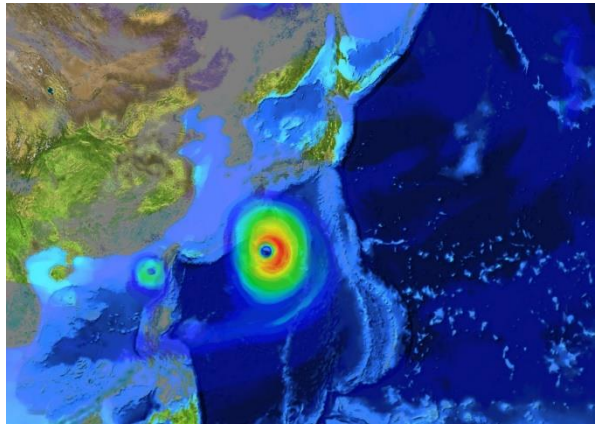
1 Hour Poster

Seongchan Kim - Senior Researcher, Korea Institute of Science and Technology Information

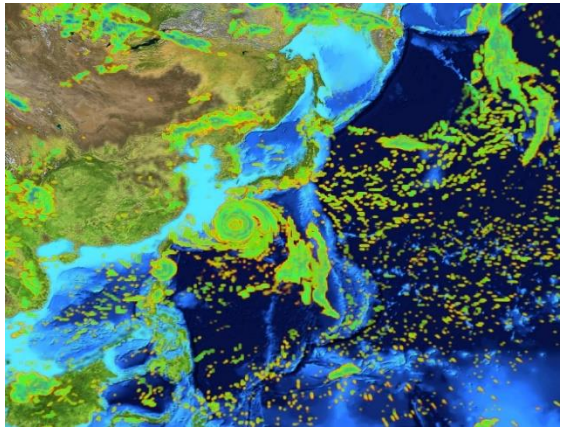
Motivation

- Today, meteorologists rely on *numerical models* to predict wind speed, precipitation, air pressure and other factors that indicate the path and intensity of a hurricane over its lifetime.
  - WRF (Weather Research and Forecasting model), MPAS (Model for Prediction Across Scales), UM (Unified Model), and CAM5 (Community Atmosphere Model ver 5.0)

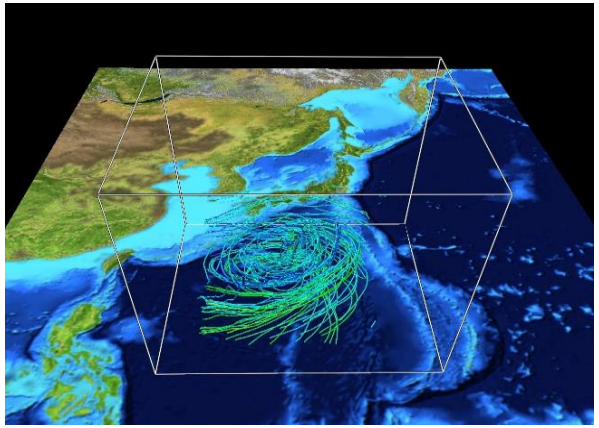




Bolaben, Wind (UVW)



Bolaben, DBz

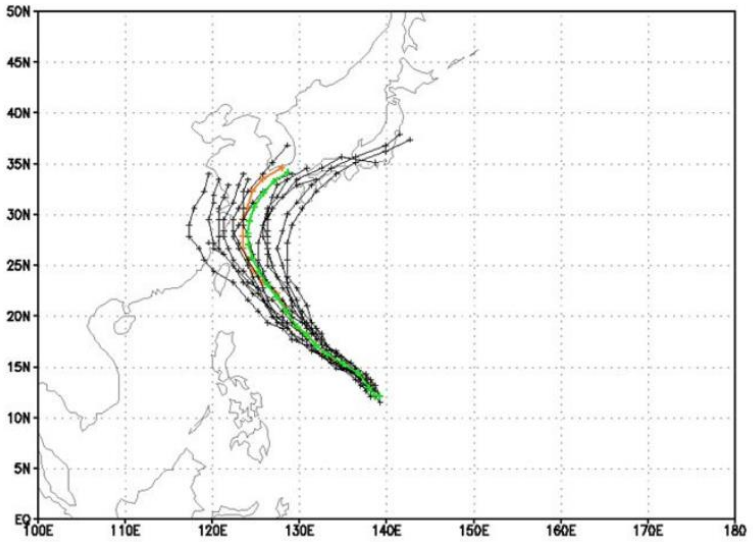


Bolaben, Flow

Visualization (Vapor)

Purpose

- **Predicting typhoon track predict** using *data from a numerical model (WRF) simulation results* with **Deep Neural Network**
  - ConvLSTM**:** Convolutional LSTM (shi et al. 2015) that learn spatial features of input data
  - Ensemble-like techniques: learning from <u>five differently conditioned WRF</u> results



Ensemble Forecasting

Data

- 10 typhoons drifting in close proximity to the Korea peninsula

No.	ID (YYNN)	Name	Period	Duration	Simulation Durations	Num. of Simulation
1	0215	루사(RUSA)	2002.08.23. 09:00 ~ 2002.09.01. 15:00	9 days 3 hours	4 days 6 hours	**25**
2	0314	매미(MAEMI)	2003.09.06. 15:00 ~ 2003.09.14. 06:00	3 days 15 hours	3 days 18 hours	**15**
3	0415	메기(MEGI)	2004.08.16. 15:00 ~ 2004.08.20. 18:00	4 days 3 hours	3 days 18 hours	**15**
4	0603	에위니아(EWINIAR)	2006.07.01. 03:00 ~ 2006.07.10. 22:00	9 days 19 hours	6 days 18 hours	**27**
5	1004	뎬무(DIANMU)	2010.08.08. 21:00 ~ 2010.08.12. 15:00	3 days 18 hours	3 days 6 hours	**13**
6	1214	뎬빈(TEMBIN)	2012.08.19. 09:00 ~ 2012.08.31. 00:00	11 days 15 hours	7 days 18 hours	**35**
7	1215	볼라벤(BOLAVEN)	2012.08.20. 15:00 ~ 2012.08.29. 06:00	8 days 15 hours	6 days 18 hours	**27**
8	1216	산바(SANBA)	2012.09.11. 09:00 ~ 2012.09.18. 09:00	7 days	4 days 18 hours	**19**
9	1509	찬홈(CHAN-HOM)	2015.06.30. 21:00 ~ 2015.07.13. 06:00	12 days 9 hours	5 days 18 hours	**23**
10	1618	차바(CHABA)	2016.09.28. 03:00 ~ 2016.10.02. 15:00	5 days 12 hours	3 days 6 hours	**13**
					Sum	**212**

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Data

- Selected variables
  - 5 variables deemed to be the most significant for cyclone tracking
  - four-dimensional
    - Time, height, width, and length
    - represented in 3-D spatial grids

Name	Description	Dimension	Data Dim.
T	perturbation potential temperature	(5, 29, 192, 192)	4 dimension (time, height, width, length)
P	perturbation pressure		
QVAPOR	Water vapor mixing ratio		
SST	Skin sea surface temperature	(5, 1, 192, 192)	
OLR	TOA outgoing long wave		

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Data

- Simulation Setting
  - 10 typhoons, 1060 predictions
  - For example, Rusa, 4 days 6 hours
  - Simulation every 6 hour cyclically
  - Five different initial conditions (models)
  - 212 * 5 = 1060
    - Whole WRF file size: 2.2 TB
- Data split

	# of instances	TF Record Size
Training set	600	150 Gb
Validation set	200	50 Gb
Testing set	200	50 Gb

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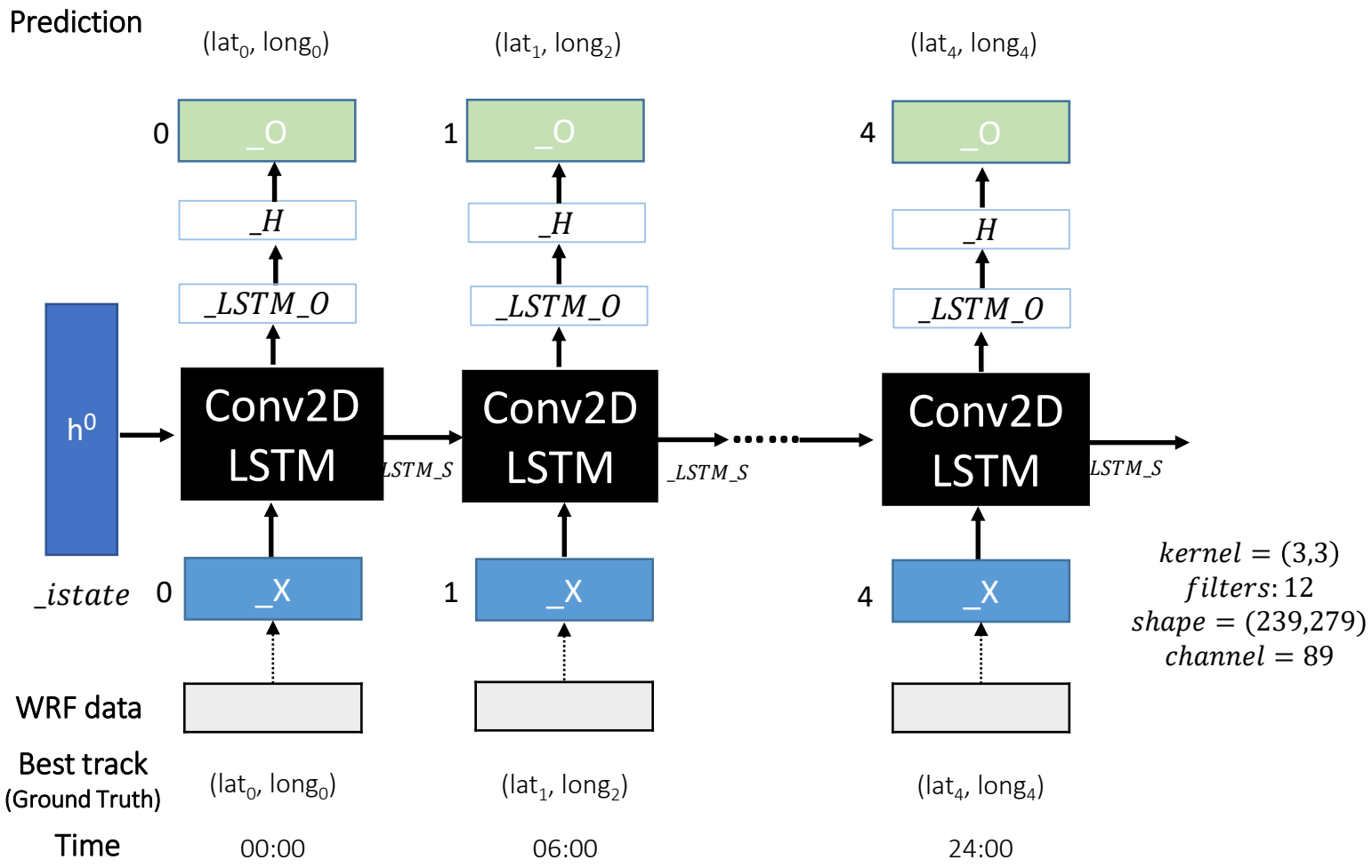
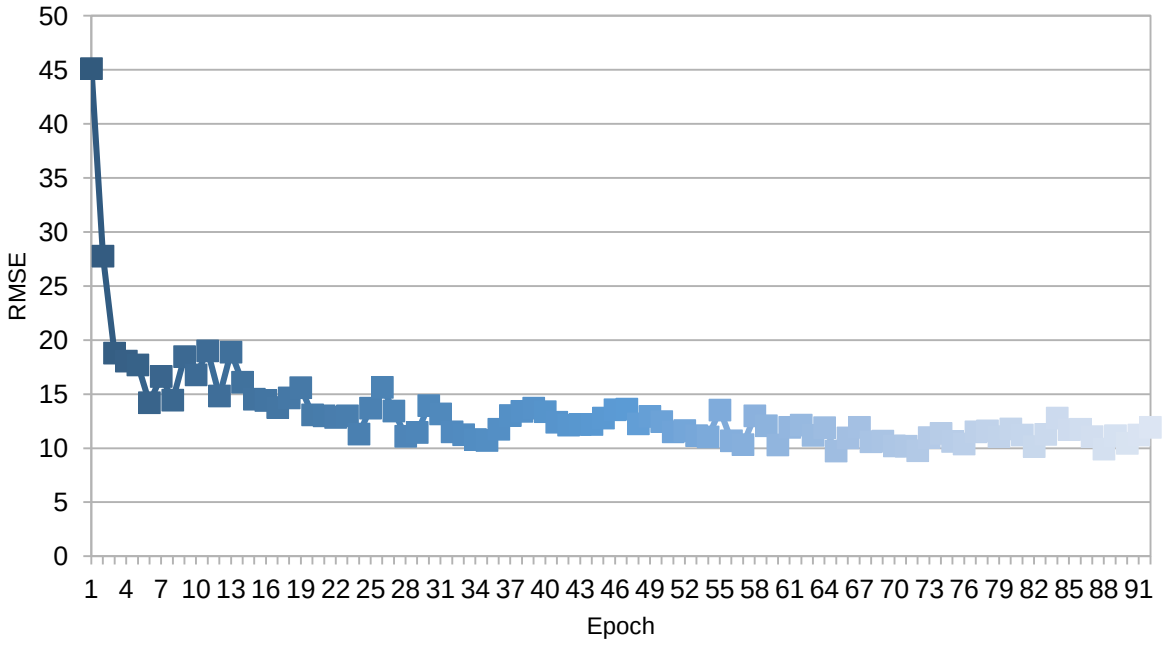
Model

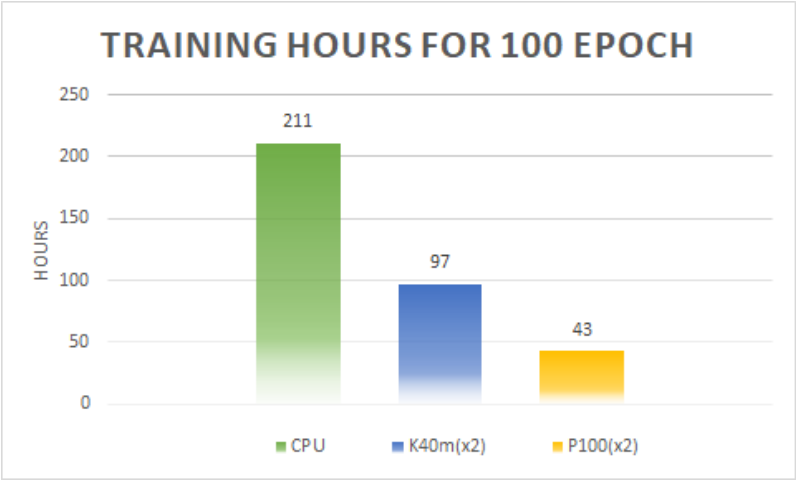
Prediction every 6 hours for *next 24 hours*



Result

- Learning





- K40m(x2) reduced 54% of training time against CPU,
- While P100(x2) reduced 56% of training time against K40m for 100 epoch

- Test Result

Model	RMSE
FC-LSTM	147.24
DeepTC: ConvLSTM	13.88

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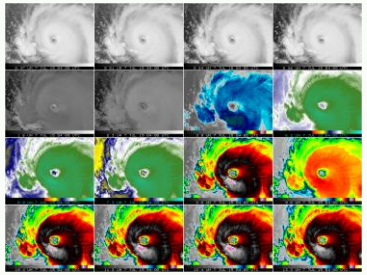
GlobeNet: Typhoon Track Prediction

Observation Data

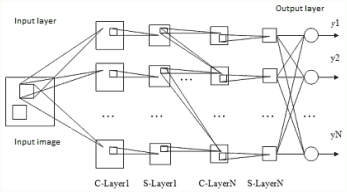
COMS–1
MI (KMA)

HIMAWARI–8
AHI (JMA)

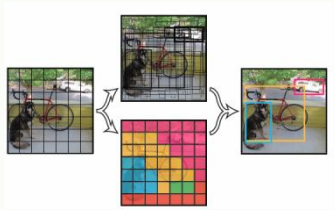


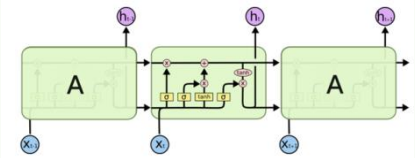
Himawari–8 images
(16ch)

Deep Learning Prediction Models



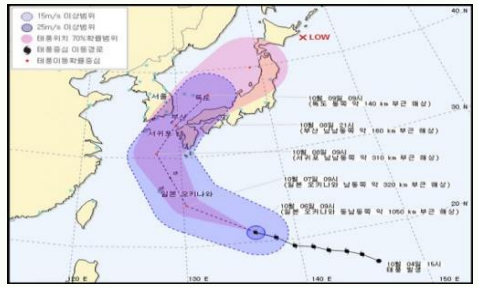
Convolutional Neural Nets
(CNNs)





Long short
Term Memory (LSTM)

Prediction of Typhoon Track



Index	Conf.	Lat	Long	hPa	NSWE
1	0.9999	27.9748	125.9390	972	N
2	0.9361	13.3122	83.7975	1013	NS
3	0	0	0	0	X
4	0	0	0	0	X
5	0	0	0	0	X
6	0	0	0	0	X

Prediction Results

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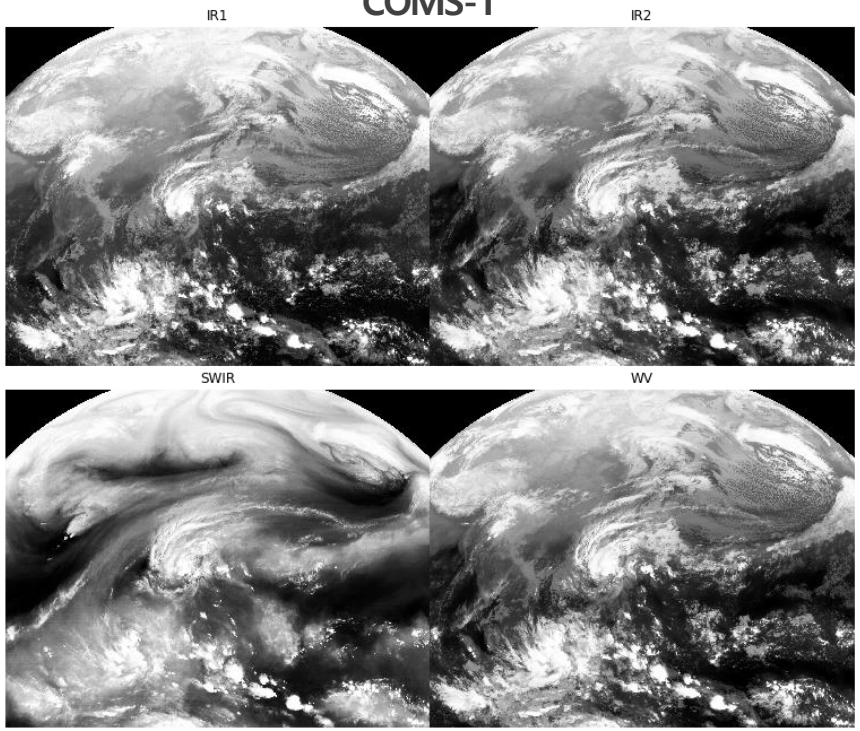
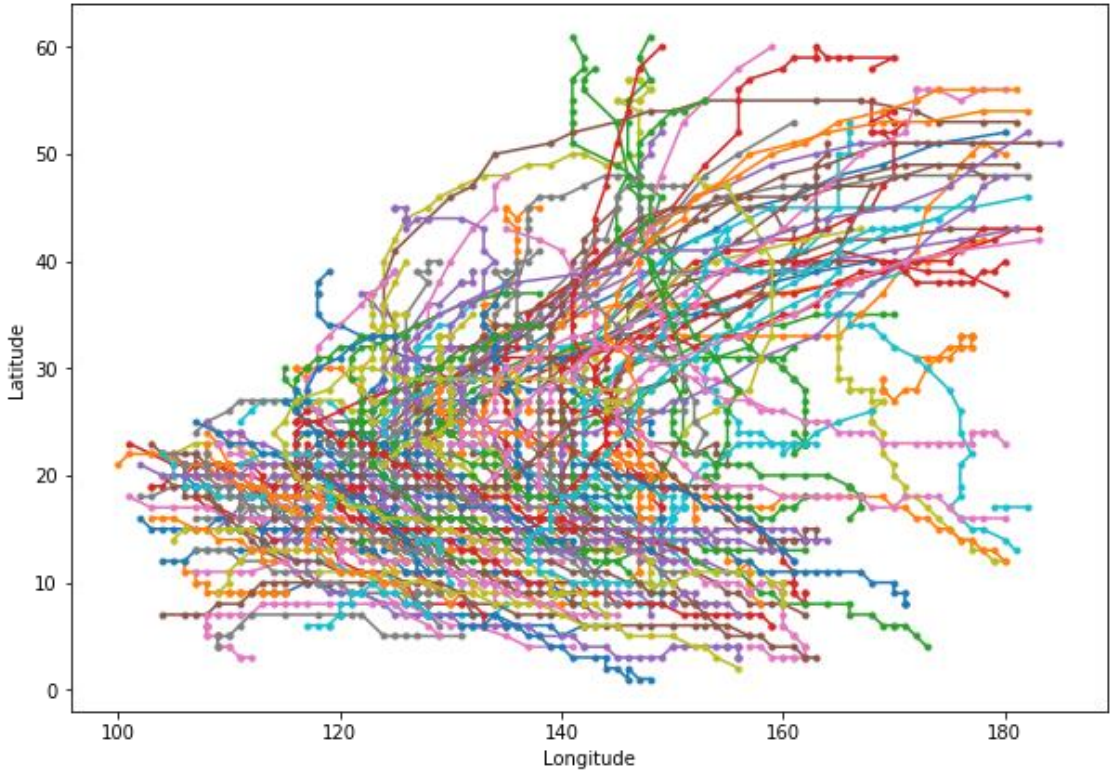
GlobeNet: Data

- Input: Satellite Data
  - COMS-1 Satellite: 4 channel(IR1, IR2, SWIR, WV)
  - Period: 2011.04~2016.12
- Label: Best Track Data
  - RSMC-Tokyo Best Track
  - 6 years: 2011~2016 (152 typhoon cases)

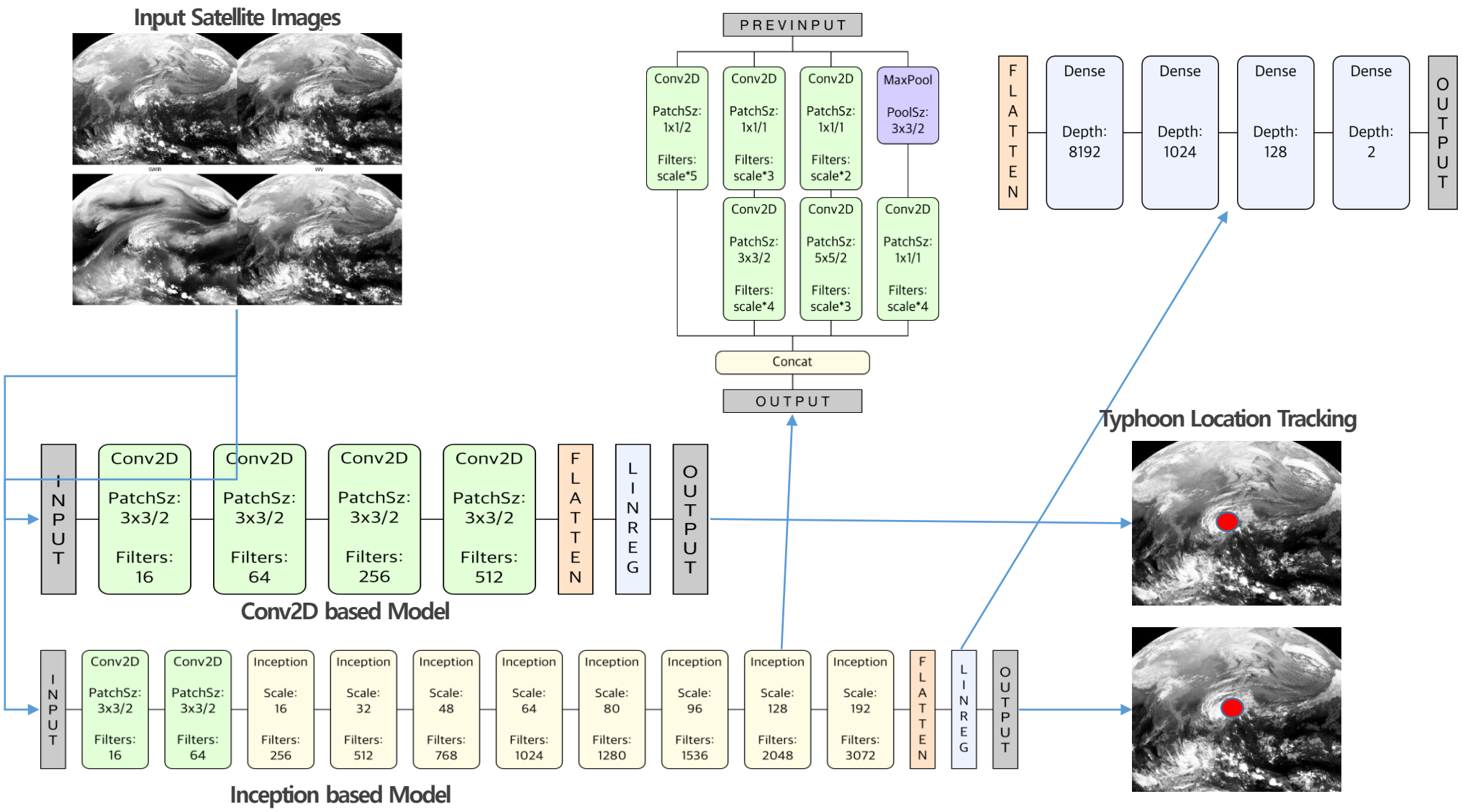
COMS-1



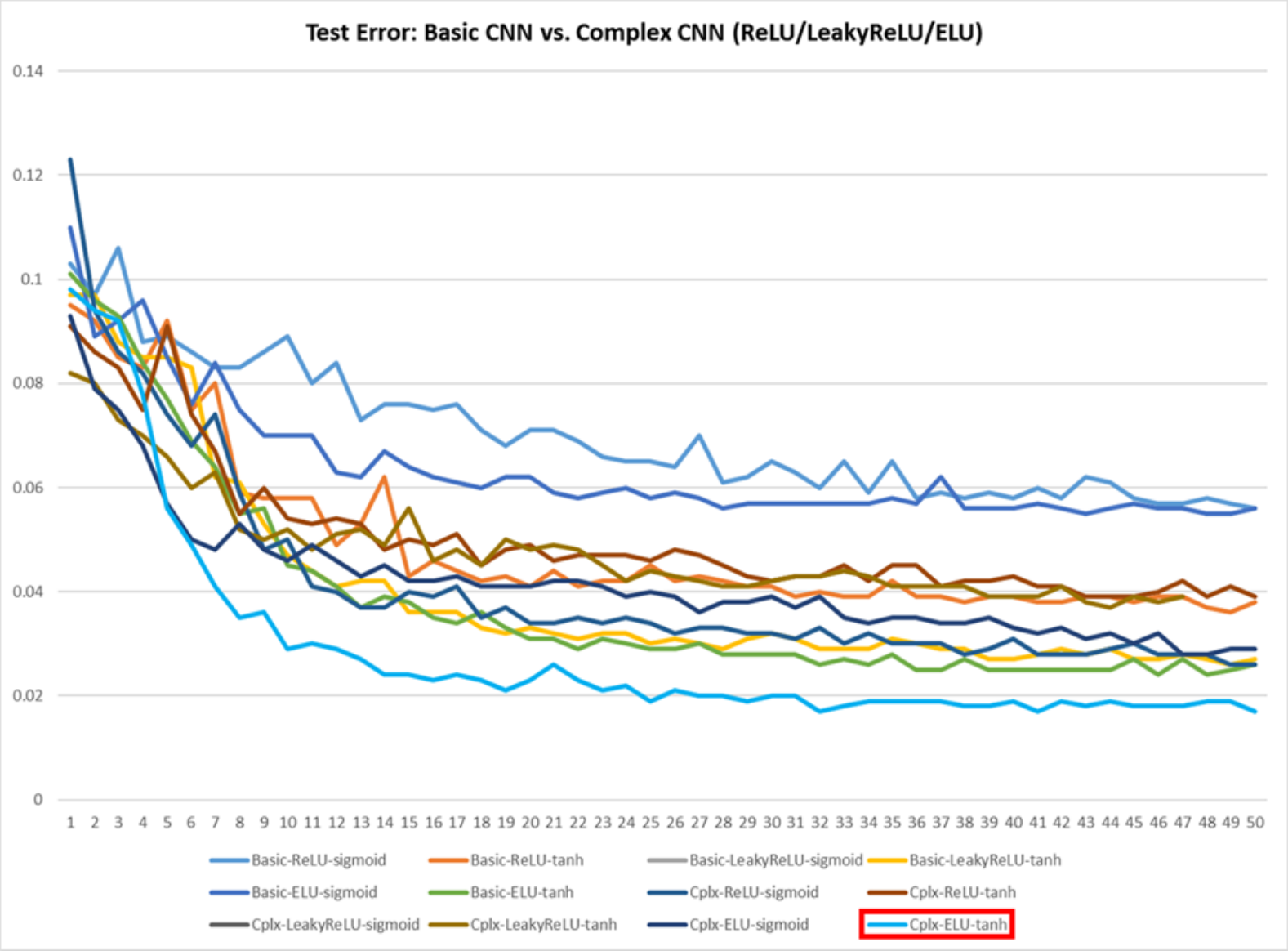
Typhoon Track



GlobeNet: Typhoon Location Detection

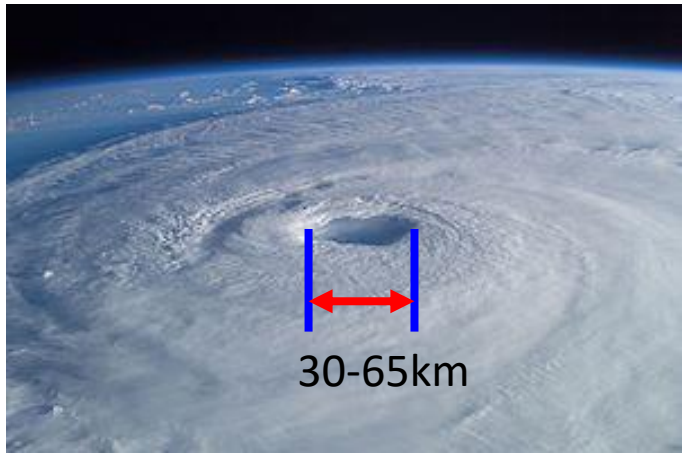


GlobeNet: Experiments



GlobeNet: Test Error

- Average Error(distance in km): 74.53 km
- Eye of typhoon: 30-65km in diameter

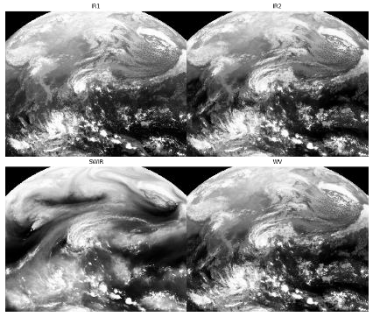


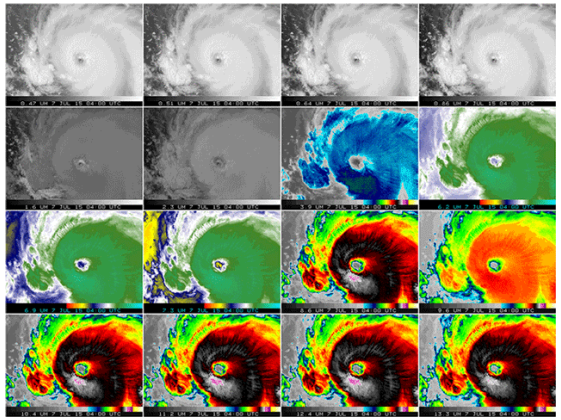
Distance(km)

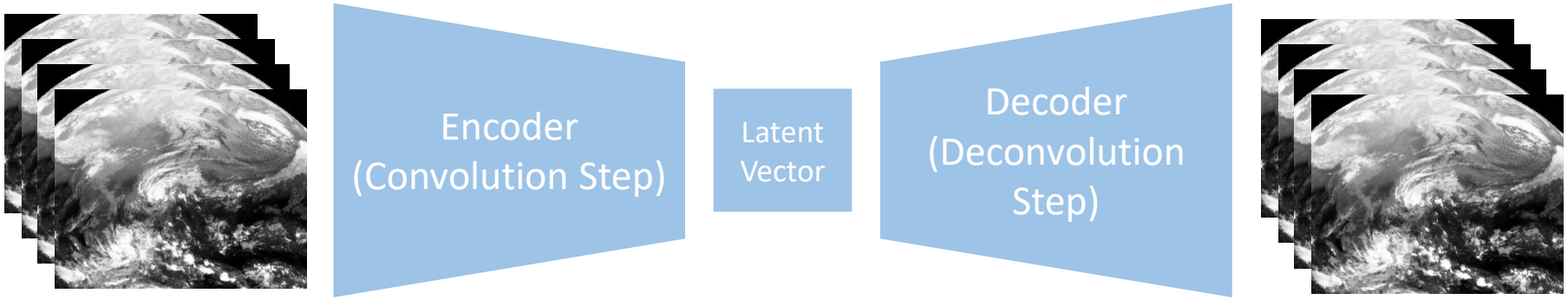
```
Dist: 320.6831625801066 | (19.789999999999999, 155.24487179487178) (18.493102312088013, 152.51905506849289)
Dist: 23.534843438839292  (12.564999999999998, 147.58589743589744) (12.563768744468689, 147.36911523342133)
Dist: 33.68556920136357 | (9.9299999999999997, 139.39871794871794) (10.154302835464478, 139.19205683469772)
Dist: 18.280318131362883  (21.829999999999998, 154.71666666666667) (21.805586218833923, 154.54159736633301)
Dist: 24.59689470492085 | (16.814999999999998, 165.01666666666665) (17.020775556564331, 165.10132813453674)
Dist: 156.59171562092385  (13.414999999999999, 157.88589743589742) (13.457308530807495, 156.4390641450882)
Dist: 1362.8092845346077  (14.350000000000001, -176.62820512820511) (14.123498916625977, 170.73157441616058)
Dist: 148.03141981313405  (8.655000000000011, 160.92307692307691) (9.626558780670166, 161.84439182281494)
Dist: 215.77863686819921  (6.2749999999999986, 136.36153846153846) (6.2972362041473389, 134.40993344783783)
Dist: 68.18267693868297 | (36.620000000000005, 150.49102564102566) (37.004326820373535, 151.08754110336304)
Dist: 82.05479286635848 | (17.070000000000004, 167.39358974358976) (16.555267095565796, 166.84150660037994)
Dist: 35.79460226302974 | (12.649999999999999, 155.37692307692311) (12.328815698623657, 155.39759695529938)
Dist: 62.11013865420944 | (21.829999999999998, 153.26410256410253) (22.141097068786621, 152.7640061378479)
Dist: 152.48602341130368  (3.2149999999999981, -179.40128205128204) (3.7351431250572205, 179.32792711257935)
Dist: 66.21814547120448 | (40.700000000000003, 179.14615384615388) (41.294760704040527, 179.11117374897003)
```

GlobeNet: Autoencoder

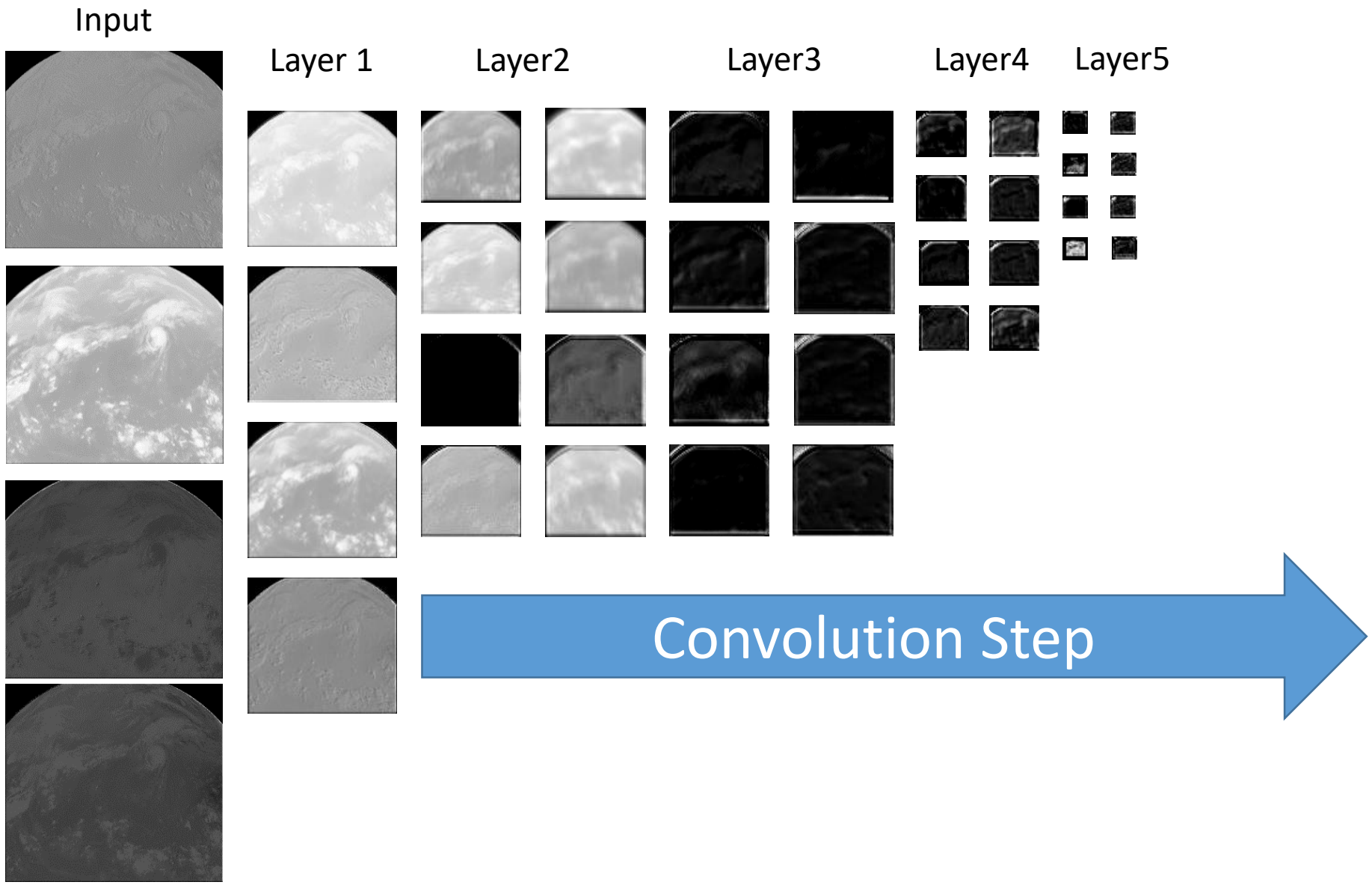
- To build a pre-trained model
- COMS-1
  - 4 channel/IR1, IR2, SWIR, WV
  - Size: 16.55 TB (2011.04~2017, 187,083 scenes)
- HIMAWARI-8 AHI
  - On-going
  - Size: hundreds of TBs
- Conv-Deconv Neural Network



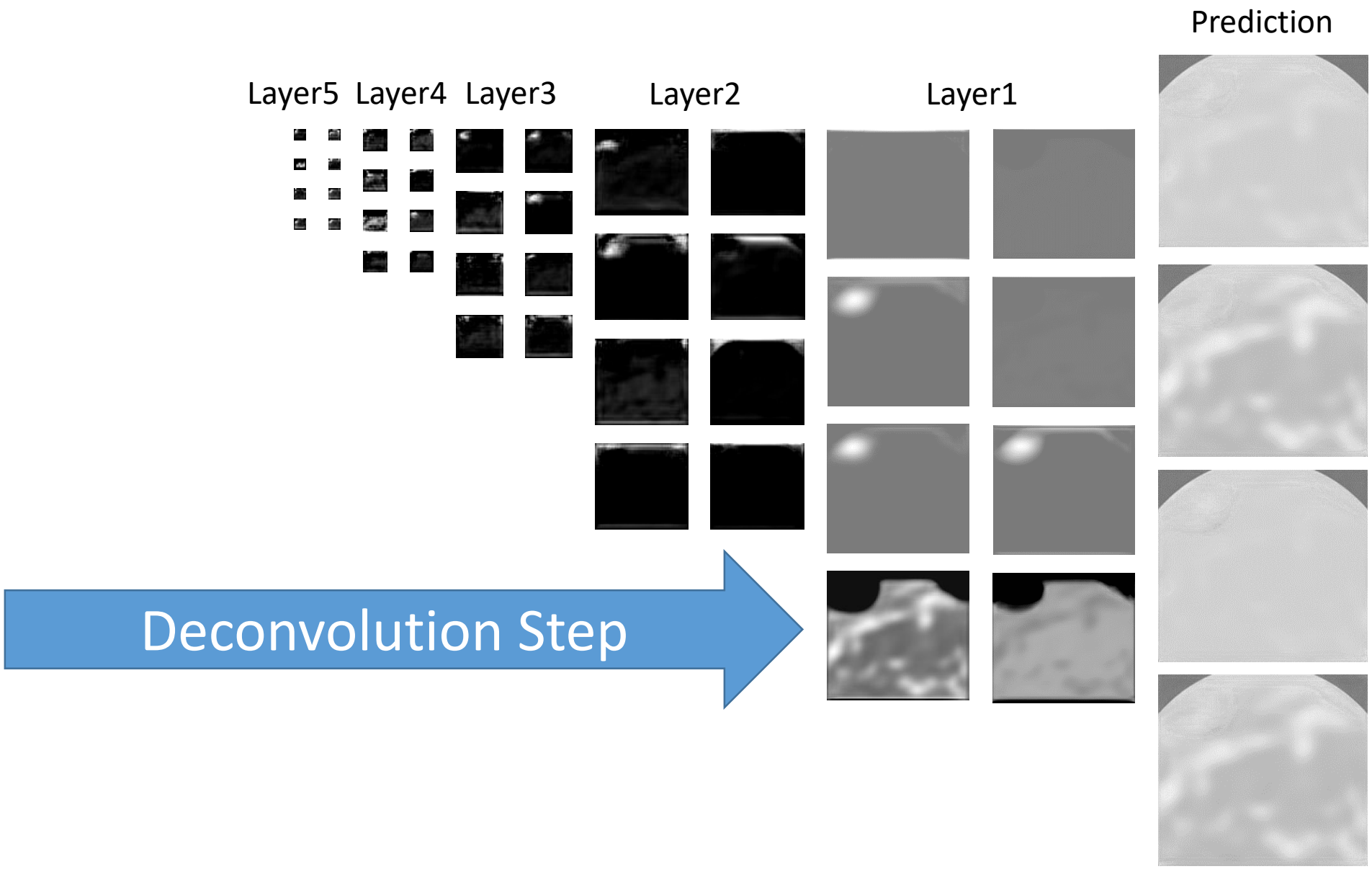




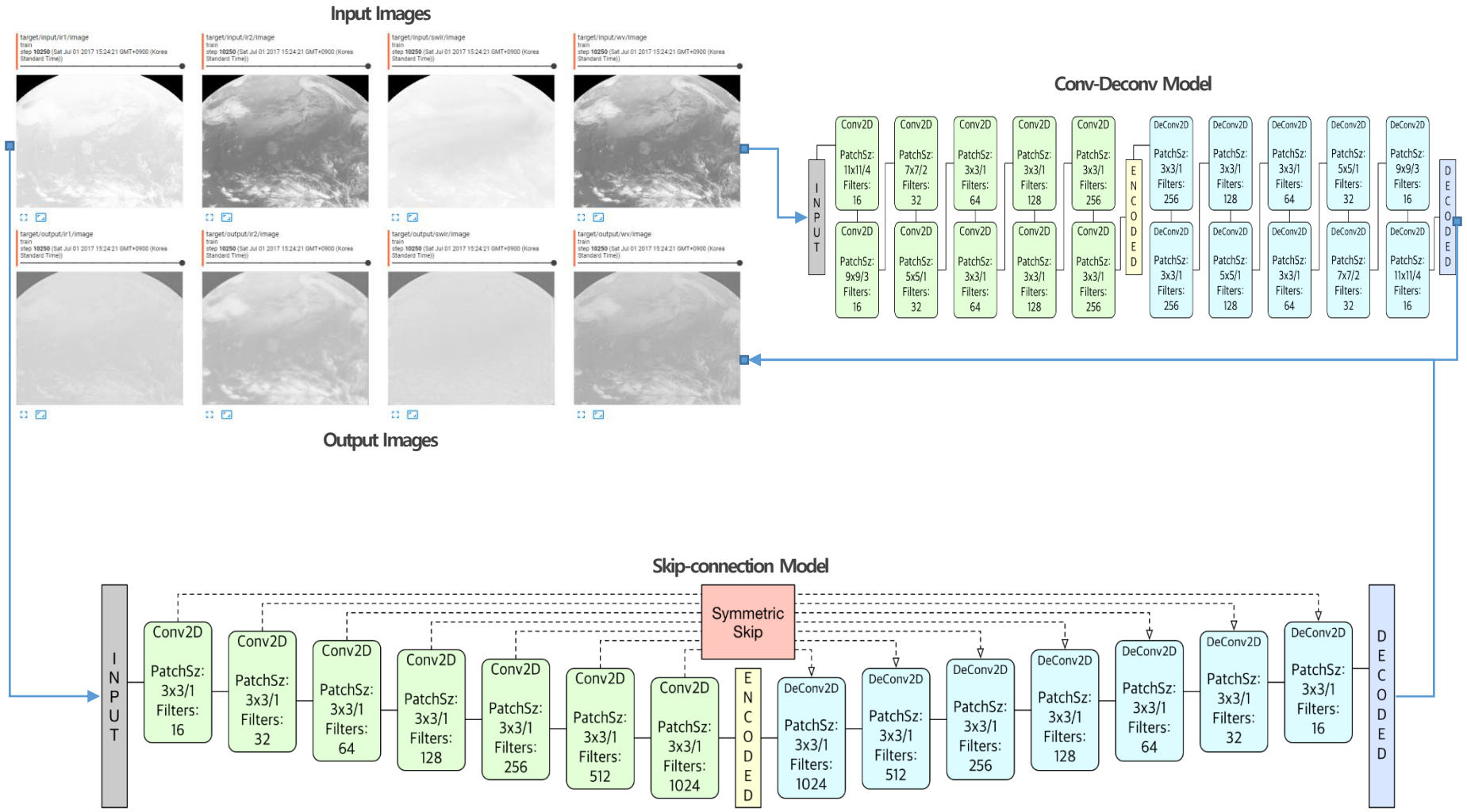
GlobeNet: Encoding Step



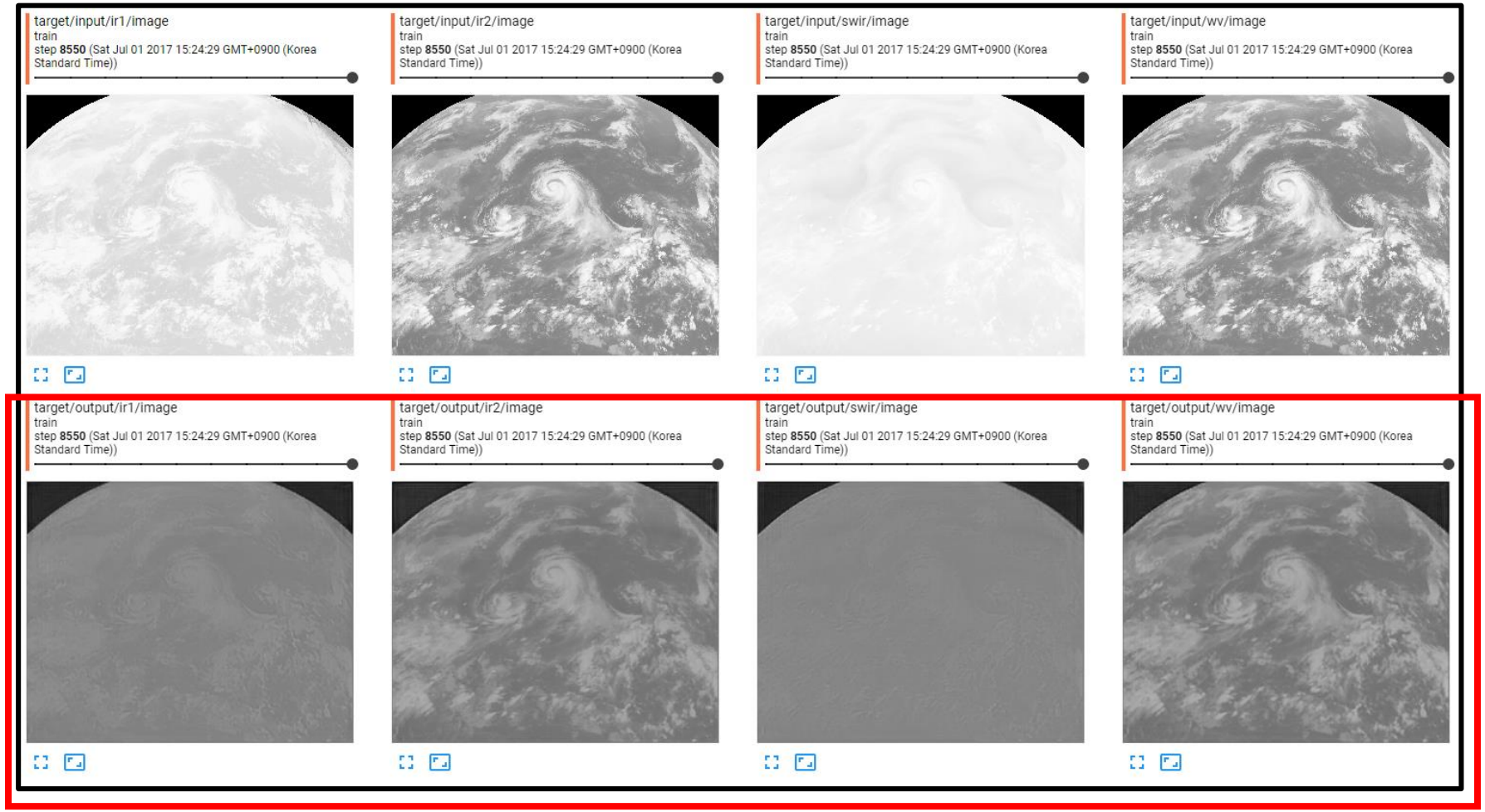
GlobeNet: Decoding Step



GlobeNet: Autoencoder



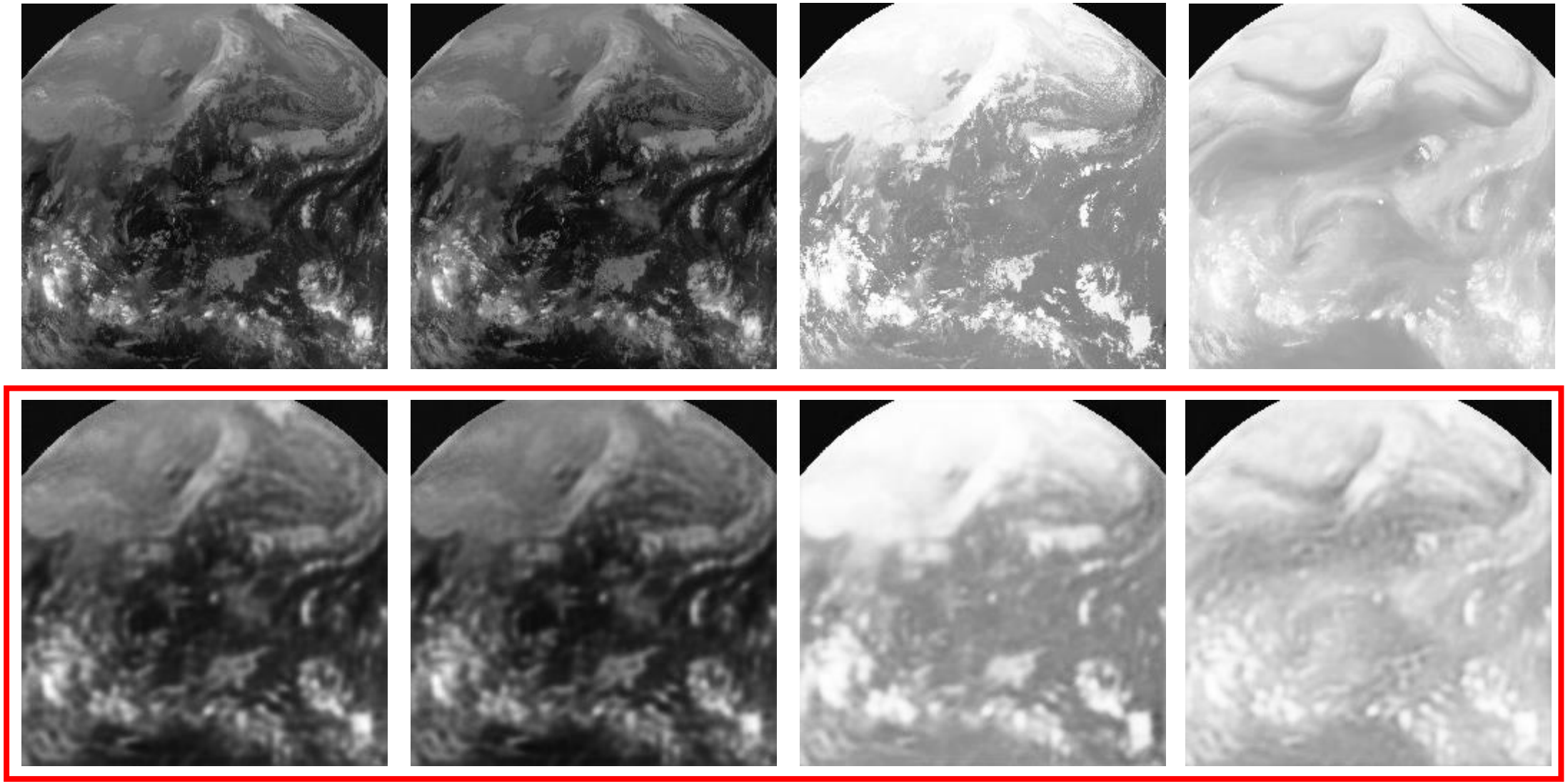
GlobeNet with Skip-connection Decoder



Output Images

Recent Convolutional AE without Skip-connection

Input Images



Output Images

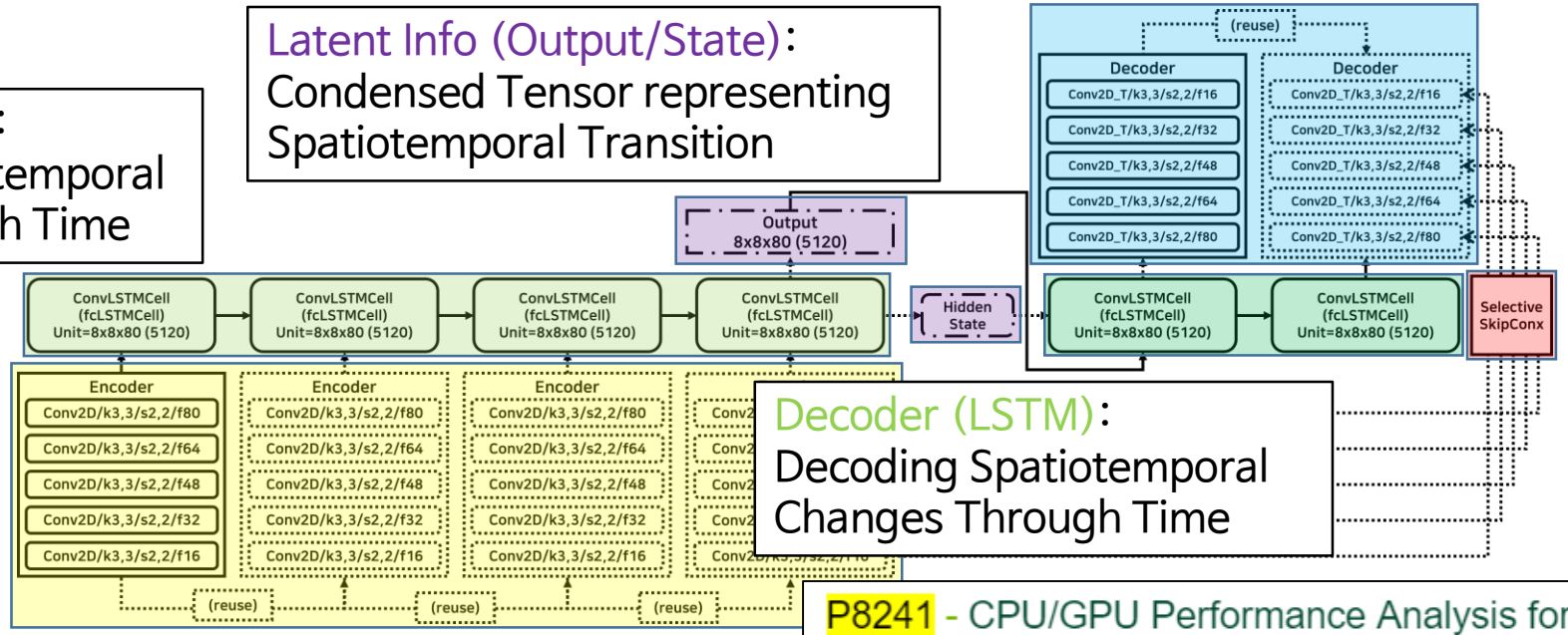
Application of Skip-connection Conv AE: PSIque

- Complex Deep Seq2Seq Autoencoder model based on Memory Network structure
- Unified model structure compatible with various RNNCells (e.g. LSTM, GRU, ConvLSTM)
- Encoder(Conv)->Encoder(LSTM)->Decoder(LSTM)->Decoder(DeConv) ⊕ SkipConx

Decoder (DeConv):
5-layers DeConvNet for Image Restoration

Latent Info (Output/State):
Condensed Tensor representing Spatiotemporal Transition

Encoder (LSTM):
Encoding Spatiotemporal Changes Through Time



Decoder (LSTM):
Decoding Spatiotemporal Changes Through Time

SkipConx:
Selective, Symmetric bypassing skip connection from Encoder to Decoder

Encoder (Conv):
5-layers ConvNet for Feature Extraction

P8241 - CPU/GPU Performance Analysis for Predicting Next Satellite Image Sequences using Convolutional Seq2Seq
1 Hour Poster
Seungkyun Hong - PhD Student/Researcher, Korea Institute of Science and Technology Information

Outline

- Introduction: Vision vs. Meteorology tasks
- Deep Learning for Weather Prediction
  - GlobeNet: Typhoon Track Prediction & Autoencoder
  - DeepRain: Prediction of Precipitation & Next Step of Images
  - DeepTC: GPU-Accelerated Trajectory Prediction for Tropical Cyclone using Traditional Numerical Model Data
- Conclusion

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Conclusion

- Deep Learning can be applied effectively to understand meteorological phenomenon
  - DeepRain does using radar reflectivity data
  - DeepTC does using numerical model data
  - GlobeNet predicts meteorological phenomenon by analyzing satellite images

- Distributed Deep Learning Platform is necessary.
- Number of associated challenges.
- Open to collaboration!!!

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Thanks

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